Conversation Intention Perception based on Knowledge Base

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Abstract. Web Intelligence is gaining its growth in a rapid speed. The notion of wisdom, which is considered as the next paradigm shift of WI, has become a hot research topic in recent years. The basic application of wisdom is making a short conversation in an interactive and understandable way based on the huge web resources. However, current conversation system normally applies the recognition of semantic similarities in the prepared database, neglecting the true intention hiding in the expression. In this paper, we present a model based on the medical Q&A knowledge base to overcome this challenge. The knowledge base includes three parts: disease entity, medicine, properties. A simple graph path algorithm based on words direction and relation weight adjustment is used to realize conversation intention perception. The experimental results show that this method can effectively perceive types of intention. This method can also be applied in deep understanding of other intelligent systems such as classifications and text mining.

Keywords: Web Intelligence, Intention Perception, Knowledge Base, Conversation System, Graph Path

1 Introduction

Web Intelligence (WI) is a new direction of academic research and industry development. The main duty of WI is making use of various web information and knowledge in a professional and effective way based on technologies such as knowledge discovery, data mining, intelligent agents as well as advanced information technology [1]. In the area of WI technology, the notion of wisdom [2] is gaining much attention in scientific research. In a simple practice, the concept of wisdom contributes to the conversation system, in which person and computer act in an unobstructed and easy manner just like the communication between human beings. This application needs to grasp the real intention of human's sentences accurately and comprehensively, which means to understand and know what his true demand is.

One traditional conversation system is to measure the semantic similarities between human inputs [3], which is not trivial to realize but the performance is

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14. ABSTRACT
Web Intelligence is gaining its growth in a rapid speed. The notion of wisdom, which is considered as the next paradigm shift of WI, has become a hot research topic in recent years. The basic application of wisdom is making a short conversation in an interactive and understandable way based on the huge web resources. However, current conversation system normally applies the recognition of semantic similarities in the prepared database, neglecting the true intention hiding in the expression. In this paper, we present a model based on the medical Q&A knowledge base to overcome this challenge. The knowledge base includes three parts: disease entity, medicine, properties. A simple graph path algorithm based on words direction and relation weight adjustment is used to realize conversation intention perception. The experimental results show that this method can effectively perceive types of intention. This method can also be applied in deep understanding of other intelligent systems such as classifications and text mining.

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unsatisfied when the input has a little word overlap. In addition, the implication of conversation always depends on the keyword's assembly among sentences. For example, about the health care consult, a patient mentioned the symptom or his information in a pretty long sentence. After all, he made clear name of medicine and want to know whether the medicine is beneficial for curing the disease, or whether it may bring side effect to his current condition. The traditional conversation system would determine the patient is talking about disease according to the symptoms and would recommend the most common treatment. The problem is that these systems cant identify customer's real intention from the given information.

The most popular online medical answering or guiding systems are mainly relied on manual consult in China. Health care system and the modern health infrastructure play an essential role in recent years [4]. However, self-management for health care has two challenges: a) building a health knowledge base with comprehensive diseases, medicine information automatically. In recent years, more and more knowledge bases with massive data are building up, such as Wikipedia [1], Wordnet [2], Baike [3] and so on. Most of these knowledge bases are established by manually editing. b) developing an intelligent consulting system which could detect customer's intention and provide some treatment recommendations within a short conversation. The applications of knowledge base for WI are still very few.

In this paper, we use massive health care Q&A data to build a health knowledge base and develop a conversation intention perception system in Chinese. The knowledge base includes three parts: disease entities, medicine entities and symptom properties. The associated relation links between them are created according to a simple graph path algorithm. We use a content center detection algorithm based on the knowledge graph to estimate the conversation intention. The experimental results show that this method can effectively perceive requirement types. This method can also be applied in deep understanding of other intelligent systems such as classifications and text mining. The main contributions of this paper are outlined as follows:

- Based on medical entities, we extracted disease entities, medicine entities, symptom entities from online resources using keyword extraction and feature selection method.
- According to the associated relations between keywords in a sentence, we proposed an automatic knowledge base building approach. We extend the association relation between entities nodes in the built knowledge base to construct the relation map and weights between nodes.
- According to the knowledge graph path and relation weight, we identify the conversation intention within a short conversation.

The main organization of this paper is listed as follows. Section 2 discusses the most related works, including stat-of-the art approaches on intention per-

[1] http://www.wikipedia.org/
[2] http://wordnet.princeton.edu/
[3] http://www.baike.com/

ception and traditional conversation system. We describe the data collection and knowledge base construction in section 3. The intention perception algorithm is explained in section 4. Section 5 illustrates the experimental performance and evaluates several factors, which may affect the performance. We summary the paper with discussion on future work in section 6.

2 Related Work

Conversation system aims at finding similar context in existing data set. Earlier works mainly focus on using the semantic similarities between sentences such as the overlap coefficient, Dice coefficient and Jaccard coefficient to get the desirable result [5]. To solve the problem that the above methods work poorly when there is little word overlap between queries, latter researches have achieved big progress using the statistical techniques of information retrieval. Jeon et al.[6] study automatic methods of finding semantically similar question pairs based on the assumption that similar answers lead to approximate questions. Ko et al.[7] apply answer relevance and answer similarity into the statistical model, and he made an improvement to this model considering correlation of the correctness of answer candidate [8]. These systems mainly rely on the semantic similarities of human inputs and neglect the user's intention implicated in them.

Intention perception is the key technology for the conversation system since the understandable machine performs well returning the answer [9]. It is a tough work considering the various human actions, and most of its researches are applied in the academic field of human-robot[10]. One of the main obstacles is that user's intention recognition contains the uncertainties, and Jeon et al.[11] proposes an ontology-based approach to minimize them. Some other research works apply the machine learning method to solve the issue. Kuan et al.[12] use the Support Vector Machine(SVM) and Linear Regression as two steps to identify human intention. Hofmann et al.[13] adopt the Bayesian belief networks to form the intention model. These methods have been proved effective in their domain.

Although context semantic and machine learning approaches have good performance in simple dialogue, it is still very difficult to deal with the new knowledge growing. On the other hand, the context-based conversation intention approach can't associate the current knowledge with linked or similar knowledge as humans. Therefore, we use a knowledge base as the fundamental element to attempt conversation intention perception.

3 Knowledge Base Building

Now, several common and large knowledge bases such as Wikipedia, MozillaZine [4], Probase [14], GeoNames[5] and WordNet [15] have been set up manually or

[4] http://kb.mozillazine.org/Knowledge_Base
[5] http://www.geonames.org/

semiautomatically. Here we use massive Q&A data set [6] to build a content based knowledge base. We use distributed web clawer to download target web page and tools like DOMTree to translate the gained Q&A information into the XML format.

3.1 Q&A Archive

URL	http://120ask.com/question/34672281.html
Question Title	Body itch
Question Body	When the summer comes, my body itch and exists red dot...
Requirement	What disease it is
Answers	It may relate to allergy which is caused by summer insects...

Table 1. structure of question and answer pair

The Q&A archive we collected are organized in Table 1. These Q&A pairs in our experiment are all Chinese. In this paper, we translate the Chinese words into English to make our examples more clear. Each item in archive has 5 fields: URL part is the unique identifier of question and answer pair. Question Title is the short description for the question and Question Body gives a detail statement about question. It is the basic data for our experiment. The average length of question body is 48 words in Chinese. Part Requirement represents the kind of help questioner is looking for. Therefore, this part contains the standard for questions' intention classification. The last part answers is the selected answer from several candidates for the corresponding question and its average length is 108 words in Chinese.

We collected 30 million Q&A pairs from the web and divided them into two collections: 25 million pairs for the training data and 5 million for the testing data. We use the requirement part to mark the training data and testing data. Phrases such as "what disease" or "how to cure" or "what medicine" or "negative influence" in the requirement part are applied to mark the question to its corresponding category. As not all the people fill in the requirement part, finally we receive nearly 1 million marked training data and 200 thousand marked testing data for our experiment. In the preprocess procedure of data set, we remove some redundant words from the questions, such as stop-words, digits and links.

3.2 Knowledge Base

To build up the knowledge base for our experiment, we need to collect three types of medical entities: disease entity, medicine entity and symptom entity. And then the relation between them is formed. The established knowledge base is the preparation and fundamental element for the next stage of experiment.

[6] http://www.120ask.com

- Disease and Drug Entities: The former two entities are professional words and obtained by web crawling. Baidu Encyclopedia (BE)[7] is an open content online encyclopedia which covers all areas of knowledge in Chinese. The Maximum entropy classifier is adopted to classify those entries into large mount of categories using structural information since the BE pages are well tagged. After receiving the labeled entities, we get nearly 25000 disease entities and 9800 medicine names.
- Symptom Entity: Since most symptom entities are not professional words and happen in the oral presentation, they can not be easily and accurately discovered from the professional encyclopedia web sites. We extract symptom entities from the collected question and answer pairs based on the assumption that most symptoms appear many times in oral presentation since patients usually have limited words to describe their diseases. Thus we extract the phrases exist frequently in question and answer pairs and then combine the phrases with the adverbs of positive and negative words. After the artificial selection we get nearly 3000 symptom entities.
- Relation Map: For the knowledge base building several relationships are identified: diseases have corresponding symptoms, diseases can be cured by corresponding medicine, symptoms can be cured by corresponding medicine. Thus, the Q&A pairs are used since the relationship of entities is hiding in them. We assume that the more frequently entities appear simultaneously in the Q&A pair, the more likely they are connected. The bigger frequency is, the closer their relationship is. After the filter process, we build up the relation map among these entities.

4 Intention Perception

The basic assumption of our model is using the medical knowledge base and relation map to adjust the keywords weights of different category intention based on correlative strength and graph path. We assume that the entity which receives more connections from other entities is more important in the conversation. Therefore, the more entities connected to the current phrase, the more weight value will be added to the current phrase.

The intention perception problem is actually a dynamic classification problem. We divide the medical questions into four types of intention, they are listed as follows:

- askers are willing to know what disease it may be
- askers are willing to know how to cure the disease or the described symptom
- askers are willing to know the medicine to cure the disease or the symptom
- askers are willing to know the negative influence of mentioned medicine

4.1 Weight Adjustment

The relation map of entities based on the knowledge base we established before is shown in Fig. 1. The double-ended arrow represents the two entities are con-

[7] http://baike.baidu.com/

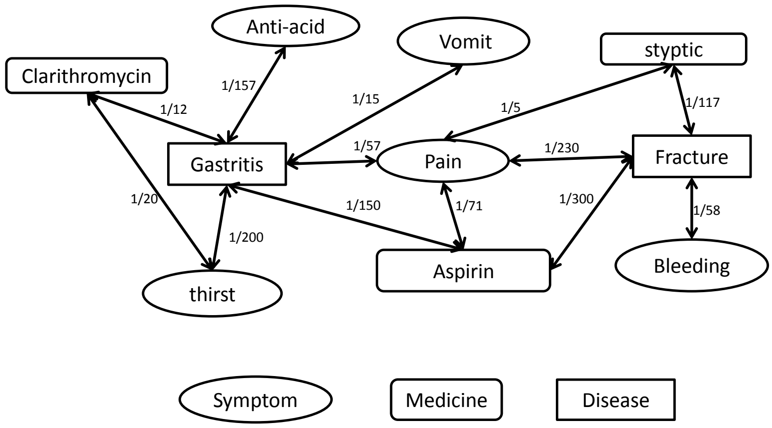

Fig. 1. The relation map of entities.

nected directly, and the digit stands for the co-occurrence frequency. Firstly, we compute the distance between two entities. For example, distance between entity Gastritis and entity Vomit is considered as one as they are connected directly, distance between entity Gastritis and entity Fracture is two since they are connected through entity Pain, while there are three units of distance between entity Gastritis and entity Bleeding. And the distance of two entities has a limitation of four. Two entities are connected within the shortest path. Secondly, when a query is given, we use Jieba Participle[8] to depart the question into phrases. The initial weight of each phrase is endowed as one. Thirdly, to a certain entity, the direct and indirect connected entities make a contribution to its weight value, we call it the contribution value. The closer distance and bigger co-occurrence of two entities both devote to larger contribution value. The formulation to compute contribution value is as follows:

$$\left(1 - \frac{1}{\log F_e}\right) * Y_X \quad (X \times Y \in R,\ R = < 1, a >, < 2, b >, < 3, c >, < 4, d >) \quad (1)$$

where F_e is the co-occurrence frequency of two entities, Y_X is the initial contribution value to the corresponding distance value X.

Considering the fact each kind of entities stands for different character of given conversation, for example, in the situation of medical system, although a symptom entity and a medicine entity both connect to a disease entity directly, their influence to the weight of disease entity is not the same, we call this influence the contribution multiplier. Fig. 2 shows the contribution multiplier we settled in our model. For instance, the contribution multiplier of medicine to disease is α, then in turn the contribution multiplier disease to medicine is $\sqrt{1-\alpha^2}$.

[8] https://pypi.python.org/pypi/jieba/

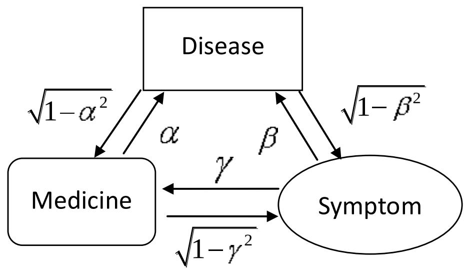

Fig. 2. The contribution multiplier between connected entities.

When come to the situation that two entities are from the same category, their distance is at least two as they can not be connected to each other directly. Their contribution multiplier is as follows:

$$contributionmultiple(A_1, A_m) = \prod_{i=1}^{m-1} contributionmultiple(A_i, A_{i+1}) \tag{2}$$

where A_1,$A_m$stand for the two entities from the same category, they are connected by the path from A_2 to A_{m-1}.

combining the contribution value and contribution multiple, we set up computational method of entity weight, it is shown as follows:

$$weight(w_i) = initialweight + \sum_{j=1,j!=i}^{n} contibution\ value * contribution\ multiple \tag{3}$$

4.2 Language Model

Language Model (LM) can be either probabilistic or non-probabilistic. The probabilistic language model is widely used in the field of data mining and natural language processing. In this paper, we adopt a probabilistic model to complete the classification task. First, we estimate the probability the subsequence of words relate to the category. Then rank the probability value and deem the category which has the highest probability is the one this question belong to.

We use $c1, c2, c3, c4$ to denote different types of intention. In order to classify the given question to which category, we need to get the question likelihood computed by $P(q|c)$, and the formulation is as follows:

$$P_r\ (q|c) = \sum_{i=1}^{N} P_r(w_i|c) \tag{4}$$

where N represents the number of words in the query and $P_r(w_i|c)$ stands for the probability word w_i occurs in current category c. The formulation we use is a multinomial distribution which indicates that the distribution of each phrase in the question is generated independently, they obey the same probability distribution. In order to compute $P_r(w_i|c)$, we assemble all the questions from the same type to one synthedic document. Then the maxmium likelihood estimate (MLE) is adopted which computes the probability as follows:

$$P_r\,(w_i|c) = \frac{F_{ic}}{F_c} \tag{5}$$

In the formulation, the F_{ic} represents the count of training data items which w_i exits and F_c is the the size of training data of the current category.

The probability of words need to be normalized to make the sum of them in all the categories to be one. Let $S_u = \sum_{i=1}^{V} P(w|c_i)$ be the normalization factor, then we recalculate the probability of words in the following rule:

$$P_r(w|c_i) = \frac{P_r(w|c_i)}{S_u} = \frac{P_r(w|c_i)}{\sum_{i=1}^{V} P_r(w|c_i)} \tag{6}$$

4.3 Combined Model

Our model combines the weight we have endowed to each phrase in the given conversation and the probability language model. The weight represents the importance of each attribute to the classification. In other words, a word with higher weight contributes more than others to the probability estimation in the classification[16]. The formulation in our model is shown as follows:

$$P_r\,(q|c) = \frac{\sum_{i=1}^{N}(weight(w_i) * P_r(w_i|c))}{\sum_{i=1}^{N} weight(w_i)} \tag{7}$$

5 Experimental Results

5.1 Data Set

In the data preparing process, we collect nearly 1 million training data and 200 thousand testing data to evaluate the proposed method. Actually, the data set for the four types of conversation is not evenly distributed, especially for the fourth category which people are looking for the negative of medicine. The detail of training data corpus is shown in Table 2. As for the testing data corpus, to be even, we equally divided it into three testing data sets, each contains 2000 articles for each category and 8000 pairs for the whole. In the later experiment, we will use these three data sets to make a comparison to ensure our model's performance.

5.2 Evaluation Measure

In our experiment, we compare our method with two basic methods, BOOL and TF-IDF. These three methods included all rely on the Equation (7), while they differ from each other the weight value in the equation. The BOOL method treats each phrase in the sentence equally. Thus the weights of phrases are all be endowed as one. Method TF-IDF is very common. It uses the term frequency and inverse category frequency value of words as its weight value. Speaking of the evaluation metrics, accuracy is adopted which is commonly seen in the field of data mining and statistics. Accuracy is a measure of the percentage that the testing data is correctly classified.

5.3 Comparison of Methods

To adopt our method, since some parameters are involved in the equation we first need to give some certain value to these parameters. In this paper, the initial contribution value $[a, b, c, d]$ is fixed and regarded as $[0.75, 0.5, 0.25, 0]$. While parameters α, β, γ are variable in the range of $[0, 1]$. Later we will adjust these variable parameters to make our model better suit to intention perception in the question.

In the given testing data, as the incomplete of knowledge base we have established, it is a fact that there might be no entity in the knowledge base can be found in the question or the found entities have no connection between each other. Facing these situations, our model will give each word the weight of one just as the BOOL method does. To see how our method works in the testing data which only involves connected entities, we remove the testing items which contain the above features and finally get nearly 11 thousand testing data pairs to form the fourth testing corpus. Thus the four testing corpus we use are as follows: the former three each contains 8 thousand items and the fourth one contains items which have connected entities.

Fig. 3 shows the comparison of three methods applied in the four different testing data corpus. In the experiment, the parameters α, β, γ are 0.7,0.9,0.9 respectively since they achieved the best result after several tests. From the figure we find that the TF-IDF method works no better than BOOL method which is reasonable as TF-IDF method is not effective in the keyword extraction when the sentence is short. While our model performs much better than these two methods especially when the data set only contains the questions which have connected entities as shown in the fourth histogram. It proves that the method we proposed can effectively grasp the central topic of question and get to know people's intention more accurately than the other two methods.

Category	Type1	Type2	Type3	Type4	Total
Data Size	165422	454036	240580	53036	913074

Table 2. training data corpus

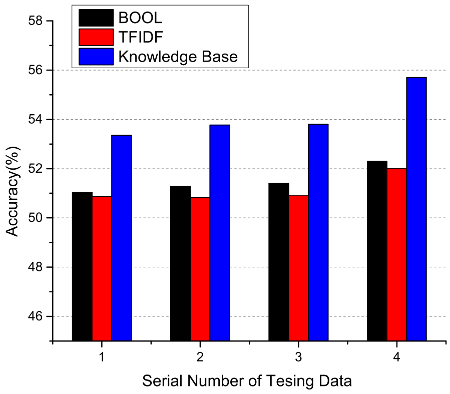

Fig. 3. The comparison of three methods in the human's intention understanding

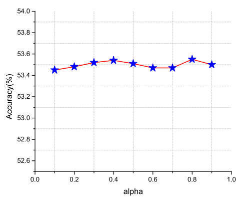

Fig. 4. The influence of alpha Parameter

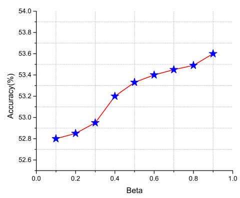

Fig. 5. The influence of beta Parameter

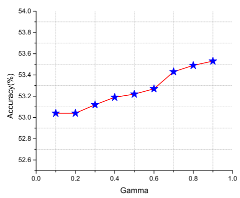

Fig. 6. The influence of gamma Parameter

5.4 Parameters Evaluation

As mentioned before, the model we adopted in this paper has a fixed set as a, b, c, d while α, β, γ are variable to optimize intention perception results. Fig. 4,5 and 6 demonstrate how the three parameters influence the accuracy of intention perception work. In every figure, the other two parameters are fixed to a static value as 0.7, so that the contribution multiple between each other is the same. It implies that the entities of medicine or disease tend to receive bigger contribution multiple parameter compare to entities of symptom which is rational since they exist less frequently than entities of symptom in a single question. Thus the former two kinds of entities are more presentative and should get a bigger contribution multiplier.

5.5 Sentence Length Effect

As we know, most sentences in conversation system are short. The number of keyword still fluctuates within a certain range. It is meaningful to measure how the three methods work when the number of words in question ranges in a given interval. We divide the testing data according to their length by steps of 20 words. From Fig. 7, we easily discovery that our method performs better than the other two when the number of words are neither too small nor too big. The small one devotes to limited number of entities while the big one contains too much information which easily makes some words over-weighted. The performance of three methods were all very low because it's difficult to extract entities. While the sentence length is over 100, the increase is not so significant for knowledge base.

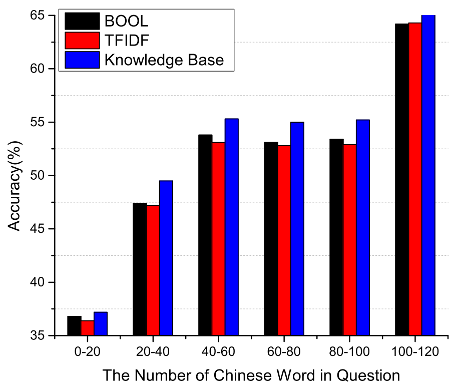

Fig. 7. The comparison of three methods in question of different length

6 Conclusion

In this paper, we crawled massive health conversation content to build a health care knowledge base. After word segmentation, keywords were extracted and symptom entities were selected using the feature candidate algorithm. The health care knowledge was built based on the association relation between diseases, medicine and symptom entities. We proposed a simple graph path and weight calculation algorithm to modify the association relation and transmission weights to estimate the intention center words. We used a Bayesian model to estimate the customers intention within short content conversation. Finally, we illustrated several experimental results with effectively perceived intention types.

Since the real conversation system likes a catch ball game, we will devote this model to build an interactive dialogue system. Furthermore, we would introduce living place, hospital name and age stage to enrich the knowledge base. And this method would be extended to other content areas such as travel consult and social network.

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